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Surface/Aerospace Surveillance Program, Surveillance, Communications, and Electronic Division, Information, Electronics and Surveillance Department

Project Title:

Unmanned Surface Sea Vehicle Power System Design and Modeling

# Final Technical Report

ONR Grant Number: N00014-04-1-0662

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November 29, 2005

## **Technical Accomplishments**

The overall goal of the present project is to develop a system-level model for a power source/energy storage mix and an intelligent power electronic control for this power source to meet a particular mission requirement for unmanned surface vehicles (USVs). In the first year of the project a few components of the power system were to be studied including a large lithium ion battery pack (suitable for USV applications) and a diesel generator (that will be combined as the power system for the USV). The original tasks also called for the design and prototyping of a rectifier/battery charger power conversion circuit to provide rapid charging of the lithium ion battery pack from the diesel generator. It was also proposed to establish an initial testbed comprising a diesel generator and a lithium ion battery pack together with a programmable dc load. However, due to time and budget constraints, the first year effort focused only on developing simulation models for the diesel generator, lithium ion battery pack, and the mechanical loads for a USV and validating the simulation models on some battery data collected both at our research facility and at the NSWCCD facility in Carderock, MD. The prototype testbed will be established as a part of the second year effort.

Li-Ion battery packs were tested using a Hybrid Pulse Power Characterization method developed for testing batteries for hybrid electric vehicle applications. Two sets of lithium ion battery packs were tested – three 70Ah Kokam cells were characterized at NSWCCD Carderock by Rebecca Smith and her colleagues, and two 5AH batteries were tested at Villanova University. The data from these measurements were used to develop accurate fuzzy logic models for the battery packs. Fuzzy logic modeling was performed using Matlab's Fuzzy Logic Toolbox to estimate the energy output and the terminal voltage of the Lithium-Ion battery. The average testing error of the energy estimated using the fuzzy logic models was around 0.2% and the average testing error used to estimate the terminal voltage of the battery pack was 0.14%.

A second model was developed in Matlab/Simulink to estimate the power developed for a diesel generator. The model comprised two submodels, one for the engine and one for the generator. The engine model was developed using the performance curves of the Caterpillar 3412C Marine engine rated at 536 kW@1800 rpm. The synchronous generator was modeled in the qd0 reference frame using the Park's transformation to study its dynamic performance.

A third model was developed in Matlab/Simulink to simulate the load on the USV. Classical equations for the static and inertial loads of a planing hull USV were implemented.

The three models for the lithium ion battery, the diesel generator and the load model were combined into a complete hybrid power system simulation model for the USV. This system level model was then used to simulate the performance of the hybrid power system for two missions – 1) an Intelligence, Surveillance and Reconnaissance (ISR) mission and 2) a Mine Countermeasure (MCM) mission. The goal was to estimate the amount of fuel would be required for these missions and to see whether the power system is able to meet the missions' power needs successfully. The fuel required to complete the

ISR mission is 195 gallons and the fuel required to complete the MCM mission is 163 gallons. Estimates of the size of the battery packs were made and found to occupy about 20% of the space in the USV for the ISR mission and 10% of the space in the USV for the MCM mission.

#### **Publications**

Three peer-reviewed conference publications emanated from this work as indicated below:

- 1. P. Singh and A. Nallanchakravarthula, "Fuzzy Logic-Based Modeling of Li-ion Batteries for HEV Applications, *Procs. EVS-21* (Monaco) April 2-6, 2005
- 2. P. Singh and A. Nallanchakravarthula, "Fuzzy Logic-Based Modeling of Hybrid Power System for Unmanned Surface Vehicles, *Intelligent Ships VI Symposium* (Villanova, PA) June 1-2, 2005
- 3. P. Singh and A. Nallanchakravarthula, "Fuzzy Logic-Based Modeling of Unmanned Surface Vehicle Hybrid Power System, *Procs.13th International Conf. on Intelligent Systems Application to Power Systems Conference*, (Arlington, VA) November 6-10, 2005 pp. 261-267

Copies of these papers are appended to this report.

## **Students Supported**

Several undergraduate and graduate students have worked on this project as indicated below:

- 1. Adithya Nallanchakravarthula, Master's level Electrical Engineering student who wrote both an independent study and a Master's thesis on this work.
- 2. Frank Kaleita, Undergraduate Electrical Engineering student
- 3. Rebecca Guercio, Undergraduate Electrical Engineering student
- 4. Rebecca Morrow, Undergraduate Electrical Engineering student

November 6-10, 2005 pp. 261-267

# Fuzzy Logic Modeling of Unmanned Surface Vehicle (USV) Hybrid Power System

Pritpal Singh, Senior Member, IEEE and Adithya Nallanchakravarthula, Student Member, IEEE

Abstract- Unmanned Surface Vehicles (USVs) can serve the roles of providing Intelligence, Surveillance and Reconnaissance (ISR) to a fleet as well as performing Mine Countermeasure (MCM) missions. Many of these missions require some period of low observable/stealth mode operation of the USV. The focus of this paper is modeling of a hybrid power system to meet for a USV to meet the mission profiles. The power system of the USV is chosen to be a hybrid power source comprising a diesel generator and a lithium-ion battery pack. Optimal sizing of the diesel generator and battery pack is important for ensuring successful USV missions. This paper describes the characterization and modeling of 70 Ah Kokam cells using fuzzy logic analysis of the experimental data to accurately estimate the SOC, power available and the terminal voltage of this Li-Ion battery. We also describe fuzzy logic-based modeling of a diesel generator. The power required to propel the USV was estimated from a planing hull drag model. This model developed in the MATLAB/Simulink environment is also described in this paper.

Index Terms-- battery model, Diesel generator, Fuzzy logic, Hybrid power system, lithium-ion, unmanned vehicles.

#### I. Introduction

Power systems for Unmanned Surface Vehicles (USVs) must provide power for vehicle propulsion and for sensors, computers, communications links, and actuators. These power systems must work autonomously and intelligently to provide the right mix of energy/power for particular missions to ensure successful mission completion and must be flexible enough to operate in stealth mode.

Hybrid power systems for vehicle propulsion consist of a combination of power sources such as diesel generator, batteries, fuel cells, etc. For the USV the hybrid power system considered here combines the power of a diesel generator and a battery pack. The battery pack is used to provide power for the USV during the stealth mode of operation. This Hybrid electric propulsion combines the heat engine and fuel tank of a conventional vehicle with the battery and electric motor of an electric vehicle. Hybrid electric vehicles turn energy into electricity while the vehicle is coasting and braking or when the diesel generator is generating more power than is required to propel the vehicle. Electricity is then stored in a battery until it is needed.

High output performance is a key requirement of batteries used in USVs. Li-Ion batteries are being used because of their high specific power/energy density and high energy efficiency.

#### A. Overview of Battery Models

There are many types of batteries and many factors that affect battery performance. To predict the performance of batteries, many different mathematical models exist. Some of the models are described in this section.

#### (1): Electrochemical Battery Models

The simplest models are based solely on electrochemistry.

(a): Peukert equation [1]

The Peukert relationship states that the discharge current of a battery decreases with increasing "constant current" discharge time.

(b): Shepherd model equation [2]

This model describes the electrochemical behavior of the battery directly in terms of voltage and current. It is often used in conjunction with the Peukert equation to obtain battery voltage and state of charge given power draw variations.

#### (2): Equivalent circuit Battery Models

Another approach to battery modeling is the use of equivalent circuits. Scientists and engineers have developed many equivalent circuit models for batteries. The charge storing capacity of the battery is often represented by a capacitor.

(a): Thévenin battery model [3]

This basic equivalent circuit consists of a voltage source (at Voc) in series with a resistor (internal resistance) and a parallel combination of a capacitor and resistor. This model is not very accurate since all of its elements can change their value depending on the condition and state of the battery.

(b): Linear electric model [4]

The linear electric model is a step above the Thévenin battery model. The open circuit voltage is applied across the voltage source and a capacitor. In series with this is a network of 3 capacitors and 3 resistors that models overcharge. In parallel to all these elements is a self-discharge resistor. Although more accurate than the Thévenin model, the components must be "replaced" as the state of the battery changes.

None of these models are completely accurate nor do any include all necessary performance-affecting factors. Furthermore many of these models require experimentally-derived curve fitting parameters that are battery specific. Fuzzy systems provide a powerful means of modeling complex

This project was supported by the Office of Naval Research (Grant No. N000140410662).

non-linear systems without the need for explicit mathematical models. In the present work, fuzzy Logic modeling has been used to predict the state-of-charge (SOC), power output and the terminal voltage (Vt) of a Li-Ion battery.

#### II. FUZZY LOGIC BASED LI -ION BATTERY MODELING

Fuzzy logic [5] can be used to predict the SOC of the battery. Battery Open Circuit Voltage (VOC) was used as the input to the Fuzzy Logic Model to estimate the battery's State-of-Charge (SOC). The power output of the battery can be estimated from the SOC of the battery.

Experimental test measurements are required to model the Li-Ion batteries. These tests help in establishing a relation between the open circuit voltage and the state-of-charge (SOC) and also between the output power and battery SOC. As the SOC of the battery varies, the open circuit voltage of the battery varies and by determining the pattern by which the voltage varies with SOC, the battery's SOC can be predicted. The variation of SOC with VOC of the battery is determined by collecting data from the battery using the Hybrid Pulse Power Characterization (HPPC) tests as specified by the Partnership for a New Generation of Vehicles (PNGV) Battery Test Manual [6].

These tests are performed at room temperature. The normal test protocol uses constant current (not constant power) at levels derived from the manufacturer's maximum rated discharge current. The characterization profile is shown in Fig. 2. The Hybrid Pulse Power Characterization (HPPC) Test profile [7] consists of an 18 s discharge, a 32 s rest, and then a 10 s Regen (charge).

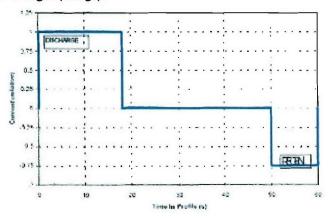


Fig.2. Pulse Power Characterization Profile

The HPPC test incorporates the pulse power characterization profile as defined above.

The test is done in the following steps

- 1. Discharge the battery completely.
- 2. Recharge the battery to its maximum capacity (i.e., 100% SOC).
- The test is made up of single repetitions of this profile, separated by 10% DOD (depth of discharge) constant current C/1 discharge segments, each

followed by a 1-hr rest period to allow the battery to return to a charge equilibrium condition before applying the next profile. The test begins with a fully charged battery after a 1-hr rest and terminates after completing the final profile at 90% DOD, discharge of the cell at a C/1 rate to 100% DOD, and a final 1hr rest.

The voltages during each rest period are recorded to establish the cell's VOC (open-circuit voltage) behavior.

#### A. Experimental Results

The HPPC test was performed on a Kokam 70 Ah Li-lon cell. The results obtained from the HPPC tests, which were run at every 10 % SOC at room temperature, can be seen in figure 3. The terminal voltage of the battery can also be seen in figure

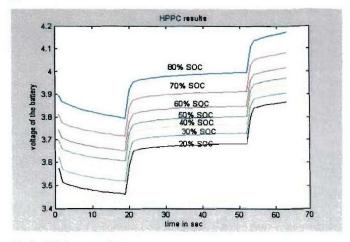


Fig.3. HPPC test results

Fuzzy logic modeling can be used to predict the SOC of the battery [8] by using the battery open circuit voltage as the single fuzzy logic model input. A second fuzzy logic model can be used to estimate the power output of the battery using the battery SOC as the sole input parameter. The power output of the battery is calculated from the terminal voltage of the battery and the load current of the battery at different SOCs.

#### B. Modeling and Simulation

Fuzzy logic models were developed to estimate the state of charge from the open circuit voltage and to estimate the power output of the Li-Ion battery from the state of charge of the battery. These models have been developed using the Fuzzy Logic Toolbox and the battery model has been implemented in the MATLAB/Simulink environment. The Matlab/Simulink battery model is shown in figure 4.

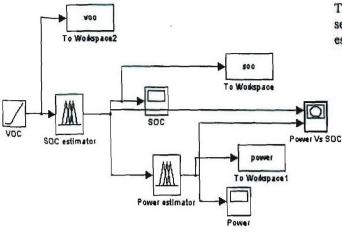


Fig.4. Li-Ion battery model in MATLAB/Simulink

#### C. SOC Estimator

The SOC estimator in the figure 4 of the battery model estimates the state of charge of the battery from the open circuit voltage of the battery. The fuzzy logic SOC estimator used Adaptive Neuro-Fuzzy training of Sugeno-type FIS. The rules generated from ANFIS SOC estimator can be seen in figure 5.

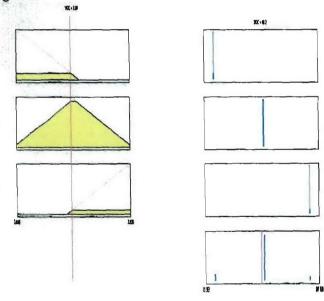


Fig.5. Rule viewer of SOC estimator

The model output (SOC) from the given input (VOC) can be seen from the surface view of the fuzzy logic based SOC estimator in figure 6.

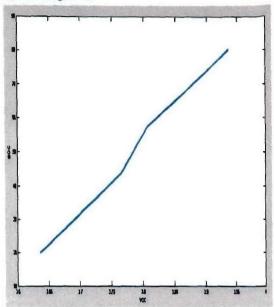


Fig.6. Surface viewer of SOC estimator

#### D. Power Estimator

The Power estimator in the figure 4 of the battery model estimates the output power of the battery from the state of charge of the battery estimated from the SOC estimator.

The fuzzy logic power estimator used Adaptive Neuro-Fuzzy training of Sugeno-type FIS. The rules generated from ANFIS Power estimator can be seen in figure 7.

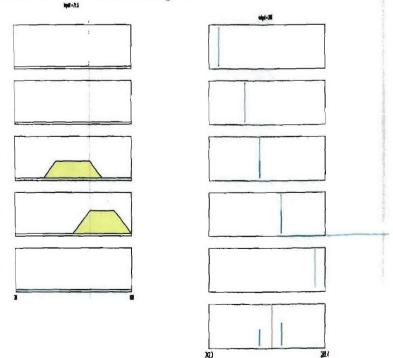


Fig.7. Rule viewer of Power estimator

The model output (SOC) from the given input (VOC) can be seen from the surface view of the fuzzy logic based SOC estimator in figure 8.

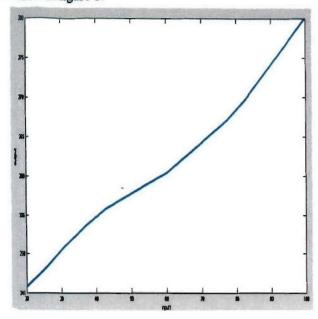


Fig.8. Surface viewer of SOC estimator

#### E. Simulation Results

The SOC, terminal voltage and the power output of the Li-Ion battery are obtained from the Simulink model. Fig. 9 shows the experimentally measured data (red asterisks) and the fuzzy logic model-predicted results (solid blue line) for the SOC estimation. Fig. 10 shows the experimentally measured data (red asterisks) and the fuzzy logic model-predicted results (solid blue line) for the output power estimation. In both the cases the error between the model-predicted results and experimentally measured results is very small (<1%).

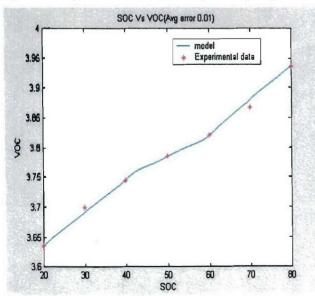


Fig.9. Experimentally measured and model-predicted estimation of state of charge of 70 ah Li-lon cell

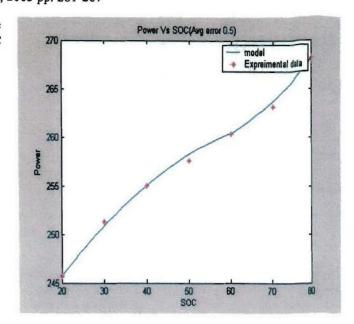


Fig.10. Experimentally measured and model-predicted estimation of power output of 70 ah Li-Ion cell

# III. FUZZY LOGIC BASED DIESEL GENERATOR MODELING [9]

From an electrical system point of view, a diesel generator can be represented as a prime mover and generator [10]. Ideally, the prime mover has the capability to supply any power demand up to rated power at constant frequency. The synchronous generator connected to it must be able to keep the voltage constant at any load condition. The Prime mover, which is the diesel engine rated at 485KW, has been modeled from the Performance curves of the 3412C Marine engine, Arating obtained from the manufacturer Caterpillar.

The Speed of the Diesel engine is estimated from the Fuel consumption of the engine and the mechanical torque is estimated using fuzzy logic. The diesel engine model developed in MATLAB/Simulink can be seen in Figure 11.

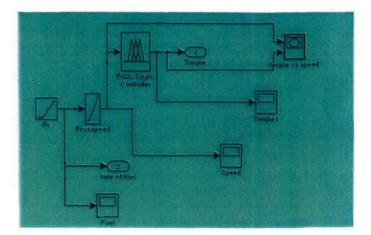


Fig.11. Diesel Engine model in MATLAB/Simulink.

## A. Fuzzy Logic based Torque Estimator

The Torque estimator in figure 11 of the diesel engine model estimates the output torque of the diesel engine from the speed of the diesel engine estimated from the lookup table FcVsspeed as shown in figure 11.

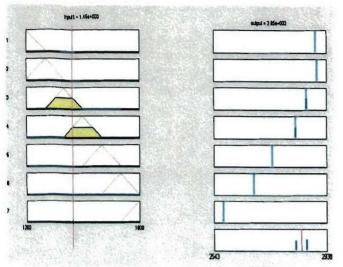


Fig.12. Rule viewer of Torque estimator

The fuzzy logic Torque estimator used Adaptive Neuro-Fuzzy training of Sugeno-type FIS. The rules generated from ANFIS Torque estimator can be seen in figure 12. The average error of the Torque estimated using fuzzy logic is around 0.002 which is a quite low value. The testing error can be seen in Figure 13.

In figure 13 the blue open circles correspond to the data that is used as the input and the red asterisks correspond to the data that is depicted by the model based on the inference.

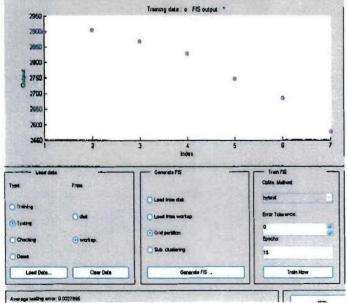


Fig.13. Testing error of the torque estimator

The Synchronous generator is also modeled MATLAB/Simulink environment. The Diesel generator, which

constitutes the diesel engine, and the synchronous generator can be seen in Figure 14.

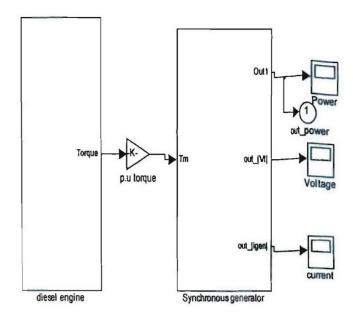


Fig.14. Diesel Generator model in MATLAB/Simulink

The Mechanical Torque vs. Speed and the Power Output vs. Fuel Consumption can be seen in Figures 15 and 16 respectively.

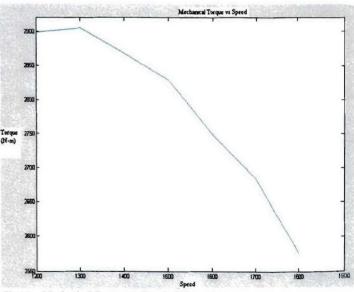


Fig.15. Mechanical Torque vs. Speed of the engine

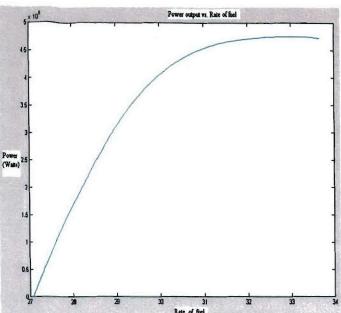


Fig.16. Power Output of the Diesel generator Vs Fuel consumption

#### III. LOAD MODELING

The load model, which is essentially the mathematical model of the drag, has to be developed to estimate amount of power required to overcome the drag. The load model is very essential in understanding the performance of the Unmanned Surface Sea Vehicle. Preliminary modeling has been done on the load model considering the displacement type of hulls. The ISR mission type of operation of the USV has been taken into consideration in developing the load model. The ISR mission consists of 6.68 hrs at high speed (45 knots) transiting to and from the mother ship (3.34 hrs each way). After the station area is reached the mission requires 336 hrs at low speed (5 knots).

The Load model developed for the ISR mission in Simulink can be seen in figure 17.

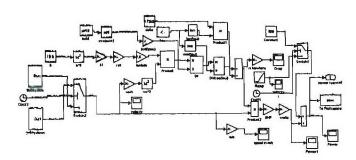


Fig 17. Load model in MATLAB/Simulink.

The Power required to overcome the drag of a planing hull [11], estimated from the load model can be seen in figure 18.

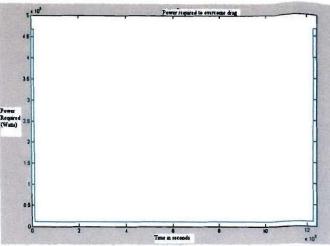


Fig. 18 Power required to overcome the drag

The initial high power is to propel the USV from the mother ship to the station area. This is followed by a period of low speed surveillance. The second peak corresponds to the high speed return of the USV back to its mother ship. The power required to drive the USV when the speed is zero is the power required to overcome the inertia of the USV. The power required to overcome the drag at 45 knots is approximately 466kW and the power required to overcome the drag at 5 knots is approximately 18kW.

#### IV. CONCLUSION

In this paper we have presented a fuzzy logic-based Li-Ion battery model which has been developed in the MATLAB/Simulink environment using experimentally collected data on a 70Ah Kokam Li-Ion cell. The model has been validated and the average error of the model is less than 1% when compared with that of the experimental data.

The fuzzy logic battery model can be upgraded to estimate the power output and SOC at different operating temperatures. The Individual models of Li-Ion battery and diesel generator as a hybrid power system for the USV have been modeled in MATLAB/Simulink environment using fuzzy logic. The power required to overcome the drag of the USV for the ISR mission has also been calculated. We are planning to add hotel load models to complete the system level hybrid power system model for the USV.

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power sources.

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devices and systems, and alternative

Adithya



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vehicles and electric vehicle propulsion system in MATLAB/Simulink environment. His current thesis research involves developing hybrid power system for Unmanned Surface Vehicle (USV).

# Dr. Pritpal Singh and Adithya Nallanchakravarthula, Villanova University Fuzzy Logic Modeling of Unmanned Surface Vehicle (USV) Hybrid Power System

#### **ABSTRACT**

Unmanned Surface Vehicles (USVs) can serve the roles of providing Intelligence, Surveillance and Reconnaissance (ISR) to a fleet as well as performing Mine Countermeasure (MCM) missions. Many of these missions require some period of the USV to operate in a low observable/stealth mode. The power system of the USV is chosen to be a hybrid power source comprising a diesel generator and a lithium-ion battery pack. Optimal design of the diesel generator, battery pack is important for ensuring successful USV missions. Fuzzy systems provide a powerful means of modeling complex non-linear systems without the need for explicit mathematical models. In this paper we describe how these battery measurements were made and how fuzzy logic analysis of the experimental data was used to accurately estimate the SOC, power available and the terminal voltage of this Li-Ion battery. Robust models of the individual components including the diesel generator and drag are also described in this paper.

#### 1 INTRODUCTION

Power systems for Unmanned Surface Sea Vehicles (USVs) must provide power for vehicle propulsion and for sensors, computers, communications links, and actuators. These power systems must work autonomously and intelligently to provide the right mix of energy/power for particular missions to ensure successful mission completion and must be flexible enough to operate in stealth mode.

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High output performance is a key requirement of batteries used in Unmanned Surface Sea Vehicles. Li-Ion batteries are being used because of their high specific power/energy density and high energy efficiency.

#### 1.1 Overview of Battery Models

There are many types of batteries and many factors that affect battery performance. To predict the performance of batteries, many different mathematical models exist. Some of the models are described in this section.

# 1.1.1 ELECTROCHEMICAL BATTERY MODELS

The simplest models are based solely on electrochemistry.

1.1.1(a) Peukert Equation [1] The Peukert relationship states that the discharge current of a battery decreases with increasing "constant current" discharge time.

Specifically

 $I^n * Ti = constant$ , where

I = discharge current [amp]

n = battery constant [number]

Ti = time to discharge at current I [seconds]

## 1.1.1(b) Shepherd Model Equation [2]

This model describes the electrochemical behavior of the battery directly in terms of voltage and current. It is often used in conjunction with the Peukert equation to obtain battery voltage and state of charge given power draw variations. Specifically:

Et = Eo - Ri\*I - Ki\*(1/(1 - f))where

Et = battery terminal voltage [volts]

Eo = open circuit voltage of a battery cell when fully charged [volts]

Ri = internal (ohmic) resistance of the battery [ohms]

Ki = polarization resistance [ohms]

Q = battery capacity [ampere-hour]

I = instantaneous current [amps]

f = integral of I\*dTIME/Qo = accumulated ampere-hours divided by full battery capacity.

The fractional state of charge is then found via Peukert's equation.

# 1.1.2 EQUIVALENT CIRCUIT BATTERY MODELS

Another approach to battery modeling is the use of equivalent circuits. Scientists and engineers have developed many equivalent circuit models for batteries. The charge storing capacity of the battery is often represented by a capacitor.

## 1.1.2(a) Thévenin Battery Model [3]

This basic equivalent circuit consists of a voltage source (at Voc) in series with a resistor

(internal resistance) and a parallel combination of a capacitor and resistor (over voltage model). This model is not very accurate since all of its elements can change their value depending on the condition and state of the battery.

#### 1.1.2(b) Linear Electric Model [4]

The linear electric model is a step above the Thévenin battery model. The open circuit voltage is applied across the voltage source and a capacitor. In series with this is a network of 3 capacitors and 3 resistors that models overcharge. In parallel to all these elements is a self-discharge resistor. Although more accurate than the Thévenin model, the components must be "replaced" as the state of the battery changes.

None of these models are completely accurate nor do any include all necessary performance-affecting factors. Furthermore many of these models require experimentally-derived curve fitting parameters that are battery specific. Fuzzy systems provide a powerful means of modeling complex non-linear systems without the need for explicit mathematical models. Fuzzy Logic modeling is done to predict the state of charge (SOC), power output and the terminal voltage (Vt) of the Li-Ion battery.

## 1.2 Introduction to Fuzzy Logic [5]

Data may be characterized in two ways: crisp or fuzzy. Crisp data describes data that is certainly indicated, e.g., a temperature of 50 °C. On the other hand fuzzy data is indicated in an uncertain way, e.g., the temperature is "warm". The linguistic descriptor can cover a range of temperatures and the degree to which a crisp data point falls into the fuzzy set of "warm" is indicated by a quantity referred to as its "degree of membership" to the set "warm".

Let us consider the range of possible temperature values as a set of all temperature. A subset of temperatures can be defined as the set of all temperatures between 20 °C and 30 °C. Let us call this subset the set of HOT

temperatures. Obviously, a measured temperature value of 25 °C can be categorized as a HOT temperature.

Not so obvious is a measured temperature value of 22.5 °C. Is this still a HOT temperature? If so, does it belong to the set of HOT temperatures as much as 25°C?

Bivalent set or crisp set theory says yes. Not only is 22.5 °C a HOT temperature, but the degree to which it belongs to the set of HOT temperatures, or its membership value or bit value (binary unit), is identical to that of 25 °C, both a value of one. It would have to be in accordance with the '1-0' theory, *i.e.* either a one or a zero.

In contrast, a fuzzy set of HOT temperatures can be defined. This fuzzy subset can cover a range of temperatures as did the bivalent set, but now the degree to which a measured data point falls into the fuzzy set of HOT is indicated by a fit value (fuzzy unit) between zero and one. The fit value is sometimes called the degree of membership. Figure.1 shows examples of various fuzzy subsets or membership functions of the temperature. Depicted is the degree of membership of various temperatures to the fuzzy subsets COLD, WARM and HOT. The process of assigning membership functions to sets of data is referred to as fuzzification of the data.

Degree of membership

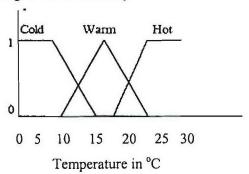


FIGURE 1: Membership function for temperature

Fuzzy set theory provides a method to categorize measured data using linguistic variables such as cold, warm and hot. It

accounts for the uncertainty inherent in such a linguistic description by using multi-valued sets.

Fuzzy systems [6] map measured inputs to desired outputs. They estimate functions by translating the behavior of the system into fuzzy sets and by using rules based on a linguistic representation of export knowledge to process the fuzzy data. This offers a qualitative rather than a numerical description of a system. The linguistic representation presents an intuitive, natural description of a system allowing for relatively easy algorithm development compared to numerical systems. The ease of development of fuzzy logic systems should not undermine their powerful capabilities in solving complex control and modeling problems.

A typical fuzzy system has four conceptual components:

- A rule base describing the relationship between input and output variables;
- A database that defines the membership functions for the input and output variables:
- A reasoning mechanism that performs the inference procedure, e.g. Mamdani or Sugeno;
- A de-fuzzification block that transforms the fuzzy output sets to a real valued output.

The rules relating the input and the output variables are written in an 'if... then' linguistic format, such as 'if temperature is hot and discharge rate is high then SOC is low'.

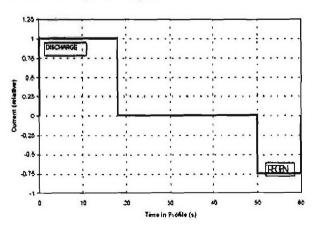
The membership functions and rule set may be described by an expert or generated by the use of neural network algorithms. Unsupervised neural networks, such as the subtractive clustering algorithm, can find the initial rules and membership functions using numerical training data that describes the input/output relationship.

# 2 FUZZY LOGIC BASED LI - ION BATTERY MODELING

The Fuzzy logic can be used to predict the SOC of the battery. Battery Open Circuit Voltage (VOC) is used as the inputs to the Fuzzy Logic Model to estimate the State of Charge (SOC). The power output of the battery can be estimated from the State of Charge (SOC) of the battery.

Experimental test measurements are required to model the Li-Ion batteries. These tests help in establishing a relation between the open circuit voltage and the state-of-charge (SOC) and also between the output power and battery SOC. As the SOC of the battery varies, the open circuit voltage of the battery varies and by determining the pattern by which the voltage varies with SOC, the battery's SOC can be predicted. The variation of SOC with VOC of the battery is determined by collecting data from the battery using the Hybrid Pulse Power Characterization (HPPC) tests as specified by the Partnership for a New Generation of Vehicles (PNGV) Battery Test Manual [7].

These tests are performed at room temperature. The normal test protocol uses constant current (not constant power) at levels derived from the manufacturer's maximum rated discharge current. The characterization profile is shown in Fig. 2. The Hybrid Pulse Power Characterization (HPPC) Test profile [8] consists of an 18 s discharge, a 32 s rest, and then a 10 s Regen (charge).



#### FIGURE 2: Pulse Power Characterization Profile

The HPPC test incorporates the pulse power characterization profile as defined above.

The test is done in the following steps

- 1. Discharge the battery completely.
- 2. Recharge the battery to its maximum capacity (i.e., 100% SOC).
- 3. The test is made up of single repetitions of this profile, separated by 10% DOD (depth of discharge) constant current C/1 discharge segments, each followed by a 1-hr rest period to allow the battery to return to a charge equilibrium condition before applying the next profile. The test begins with a fully charged battery after a 1-hr rest and terminates after completing the final profile at 90% DOD, discharge of the cell at a C/1 rate to 100% DOD, and a final 1-hr rest.

The voltages during each rest period are recorded to establish the cell's VOC (open-circuit voltage) behavior.

#### 2.1 Experimental Results

The HPPC test was performed on a Kokam 70 Ah Li-Ion cell. The results obtained from the HPPC tests, which were run at every 10 % SOC at room temperature, can be seen in figure 3. The terminal voltage of the battery can also be seen in figure 3.

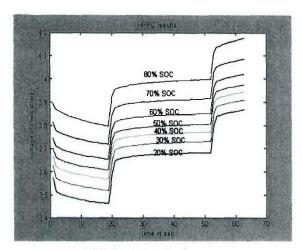
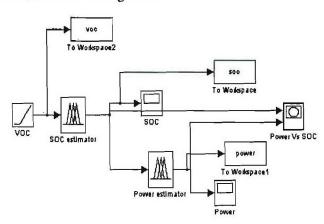


FIGURE 3: HPPC test results

Fuzzy logic modeling can be used to predict the SOC of the battery [9] by using the battery open circuit voltage as the single fuzzy logic model input. A second fuzzy logic model can be used to estimate the power output of the battery using the battery SOC as the sole input parameter. The power output of the battery is calculated from the terminal voltage of the battery and the load current of the battery at different SOCs.

#### 2.2 Modeling and Simulation

Fuzzy logic models were developed to estimate the state of charge from the open circuit voltage and to estimate the power output of the Li-Ion battery from the state of charge of the battery. These models have been developed using the Fuzzy Logic Toolbox and the battery model has been implemented in the MATLAB/Simulink environment. The Matlab/Simulink battery model is shown in figure 4.



# FIGURE 4: Li-Ion battery model in MATLAB/Simulink

#### 2.3 Simulation Results

The SOC, terminal voltage and the power output of the Li-Ion battery are obtained from the Simulink model. 5 Fig. shows experimentally measured data (red asterisks) and the fuzzy logic model-predicted results (solid blue line) for the SOC estimation. Fig. 6 shows the experimentally measured data (red asterisks) and the fuzzy logic model-predicted results (solid blue line) for the output power estimation. In both the cases the error between the model-predicted results and experimentally measured results is very small (<1%).

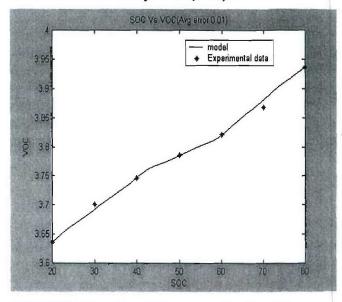


FIGURE 5: Experimentally measured and modelpredicted estimation of state of charge of 70 ah Li-Ion cell

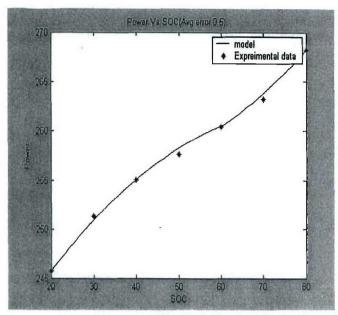


FIGURE 6: Experimentally measured and modelpredicted estimation of power output of 70 ah Li-Ion cell

# 3 FUZZY LOGIC BASED DIESEL GENERATOR MODELING [10]

From an electrical system point of view, a diesel generator can be represented as a prime mover and generator [11]. Ideally, the prime mover has the capability to supply any power demand up to rated power at constant frequency.

The synchronous generator connected to it must be able to keep the voltage constant at any load condition. The Prime mover, which is the diesel engine rated at 339KW, has been modeled from the Performance curves of the 6125 Marine engine, M3 obtained from the manufacturer John Deere.

The Speed of the Diesel engine is estimated from the Fuel consumption of the engine and the mechanical torque is estimated using the fuzzy logic.

The diesel engine model developed in MATLAB/Simulink can be seen in Figure 7.

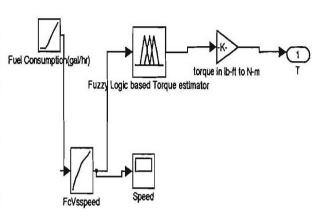
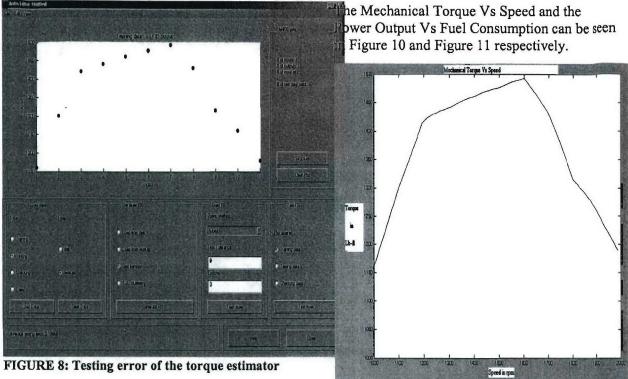


FIGURE 7: Diesel Engine model in MATLAB/Simulink.

The average error of the Torque estimated using fuzzy logic is around 0.19 which is a quite low value. The testing error can be seen in Figure 8.

In the figure the blue open circles correspond to the data that is used as the input and the red asterisks correspond to the data that is depicted by the model based on the inference.



The Synchronous generator is also modeled in MATLAB/Simulink environment. The Diesel generator, which constitutes the diesel engine, and the synchronous generator can be seen in Figure 9.

FIGURE 10: Mechanical Torque Vs Speed of the engine

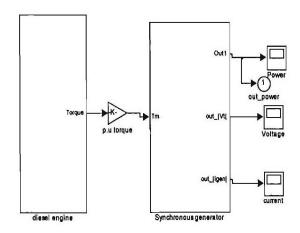


FIGURE 9: Diesel Generator model in MATLAB/Simulink

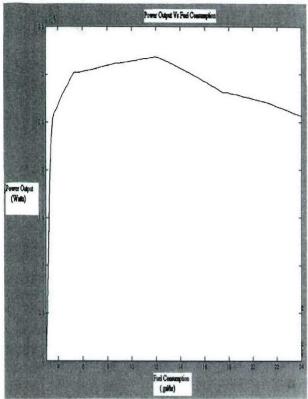


FIGURE 11: Power Output of the Diesel generator Vs Fuel consumption

#### 4 LOAD MODELING

The load model, which is essentially the mathematical model of the drag, has to be developed to estimate amount of power required to overcome the drag.

The load model is very essential in understanding the performance of the Unmanned Surface Sea Vehicle. Preliminary modeling has been done on the load model considering the displacement type of hulls. The typical operation of the USV (acceleration constant speed then deceleration) has been taken into consideration in developing the load model.

The Load model developed in MATLAB/Simulink environment can be seen in Figure 12.

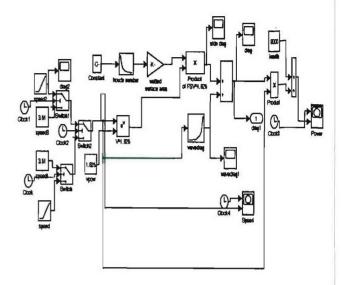


FIGURE 12: Load model in MATLAB/Simulink.

The Power required to overcome the drag of a displacement hull, estimated from the load model can be seen in Figure 13.

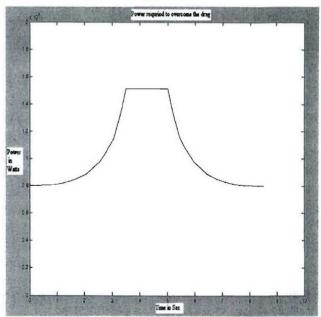


FIGURE 13: Power required to overcome the drag

In figure 13 the power required to drive the USV when the speed is zero is the power required to overcome the inertia of the USV. The speed variation of the USV (acceleration

constant speed then deceleration) can be seen in figure 14.

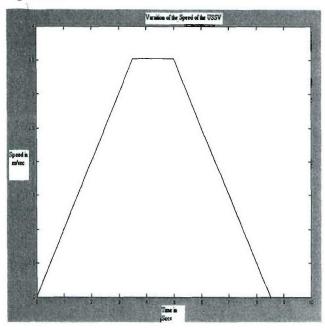


FIGURE 14: Speed variation of the USV

The maximum speed of a displacement hull of length 10 meters is 3.51m/s. The planning type of hulls can travel much faster than the displacement hulls .The maximum speed of the USV (planing hull) is around 23.67 m/s for the same length of 10 meters.

#### CONCLUSION

In this paper we have presented a fuzzy logicbased Li-Ion battery model which has been developed in the MATLAB/Simulink environment using experimentally collected data on 70Ah Kokam Li-Ion cell. The model has been validated and the average error of the model is less than 1% when compared with that of the experimental data. The fuzzy logic battery model can be upgraded to estimate the power output and SOC at different operating temperatures. The Individual models of the Li-Ion battery, diesel generator and the load of the USV have been modeled in MATLAB/Simulink environment using fuzzy logic. The fuzzy logic approach is robust, accurate and reliable. We are planning to integrate these models into a system level hybrid power system for the unmanned surface sea vehicle.

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Dr. Pritpal Singh is the principal author and he is an Associate Professor and Assistant Chairperson of the ECE Department, Villanova University. Pritpal Singh received his B.Sc from the Univ. of Birmingham, U.K. and Ph.D. from the Univ. of Delaware. He is an Associate Professor of Electrical Engg. at Villanova University where his research is focused on and fuel SOC/SOH of batteries cells, photovoltaic devices and systems. alternative power sources.

Adithya Nallanchakravarthula received his B.E in Electrical and Electronics at University College of Engineering, Osmania University, Hyderabad, India. He is currently pursuing his MS in Electrical Engineering at Villanova University, PA, USA. He worked on fuzzy logic based speed control of electric vehicles and electric vehicle propulsion system in MATLAB/Simulink environment. His current

thesis research involves developing hybrid power system for Unmanned Surface Sea Vehicle (USV).

# Fuzzy Logic Modeling of Li-ion Batteries for HEV Applications

# Pritpal Singh and Adithya Nallanchakravarthula Villanova University

#### Abstract

Li-ion batteries hold the promise of being used in hybrid electric vehicles (HEVs) because of their high specific power/energy and high energy efficiency. Robust models of the Li ion battery need to be developed in order to accurately simulate HEV performance. Fuzzy systems provide a powerful means of modeling complex non-linear systems, such as batteries, without the need for explicit mathematical models. Several tests were run on a 70Ah Li-ion cell to model the State of charge (SOC) and power available from the battery. In this paper we describe how these battery measurements were made and how fuzzy logic analysis of the experimental data was used to accurately estimate the SOC, power available and the terminal voltage of this Li-ion battery.

Keywords: lithium-ion, battery model, HEV (hybrid electric vehicle), simulation.

#### 1. Introduction

Hybrid electric vehicles (HEVs) combine the heat engine and fuel tank of a conventional vehicle with the battery and electric motor of an electric vehicle. This combination offers the extended range and rapid refueling that consumers expect from a conventional vehicle, with a significant portion of the energy and environmental benefits of an electric vehicle. The inherent flexibility of HEVs allow for their use in a wide range of applications including personal transportation, public transit, and commercial hauling. HEVs turn energy into electricity while the vehicle is coasting and braking. Electricity is then stored in a battery until it's needed. High output performance is a key requirement of HEV batteries. The performance of the battery pack in HEVs is critical to the vehicle's performance and energy management strategies. Advanced battery systems are being used in HEVs. Among them Li ion batteries are being proposed because of their high specific power/energy density and high energy efficiency.

#### 1.1 Overview of Battery Models

There are many types of batteries and many factors that affect battery performance. To predict the performance of batteries, many different mathematical models exist. Some of the models are described in this section.

#### 1.1.1 Electrochemical Battery Models

The simplest models are based solely on electrochemistry.

#### 1.1.1(a) Peukert Equation [1]

The Peukert relationship states that the discharge current of a battery decreases with increasing "constant current" discharge time. Specifically

 $I^n * Ti = constant$ 

where

I = discharge current [amp]

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## 1.1.1(b) Shepherd Model Equation [2]

This model describes the electrochemical behavior of the battery directly in terms of voltage and current. It is often used in conjunction with the Peukert equation to obtain battery voltage and state of charge given power draw variations. Specifically:

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where

Et = battery terminal voltage [volts]

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Ri = internal (ohmic) resistance of the battery [ohms]

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Q = battery capacity [ampere-hour]

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f = integral of I\*dTIME/Qo = accumulated ampere-hours divided by full battery capacity.

The fractional state of charge is then found via Peukert's equation.

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Another approach to battery modeling is the use of equivalent circuits. Scientists and engineers have developed many equivalent circuit models for batteries. The charge storing capacity of the battery is often represented by a capacitor.

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None of these models are completely accurate nor do any include all necessary performance-affecting factors. Furthermore many of these models require experimentally-derived curve fitting parameters that are battery specific. Fuzzy systems provide a powerful means of modeling complex non-linear systems without the need for explicit mathematical models. This paper considers the modeling of a Li-ion battery employed as a part of the hybrid power source for the HEV. Fuzzy Logic modeling is done to predict the state of charge (SOC), power output and the terminal voltage (Vt) of the Li ion battery.

#### 1.2 Introduction to Fuzzy Logic [5]

Data may be characterized in two ways: crisp or fuzzy. Crisp data describes data that is certainly indicated, e.g., a temperature of 50 °C. On the other hand fuzzy data is indicated in an uncertain way, e.g., the temperature is "warm". The linguistic descriptor can cover a range of temperatures and the degree to which a crisp data point falls into the fuzzy set of "warm" is indicated by a quantity referred to as its "degree of membership" to the set "warm".

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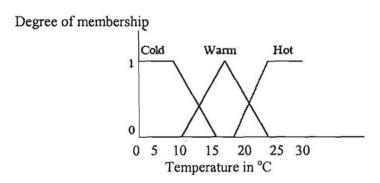


Figure 1: Membership function for temperature

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Experimental test measurements are required to model the Li-ion batteries. These tests help in establishing a relation between the open circuit voltage and the state-of-charge (SOC) and also between the output power and battery SOC. As the SOC of the battery varies, the open circuit voltage of the battery varies and by determining the pattern by which the voltage varies with SOC, the battery's SOC can be predicted. The variation of SOC with OCV of the battery is determined by collecting data from the battery using the Hybrid Pulse Power Characterization (HPPC) tests as specified by the Partnership for a New Generation of Vehicles (PNGV) Battery Test Manual [7].

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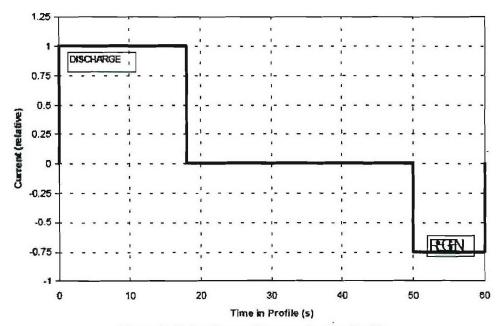


Figure 2: Pulse Power Characterization Profile

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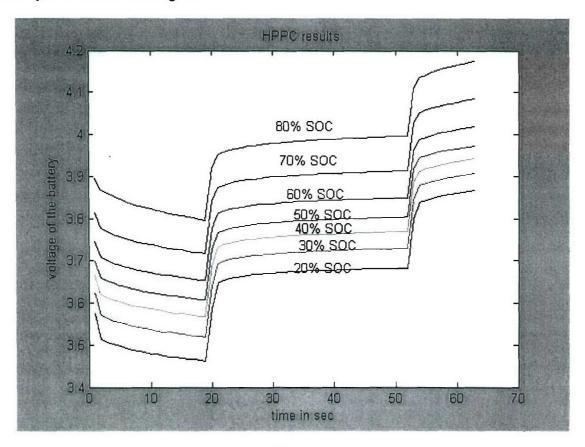


Figure 3: HPPC test results

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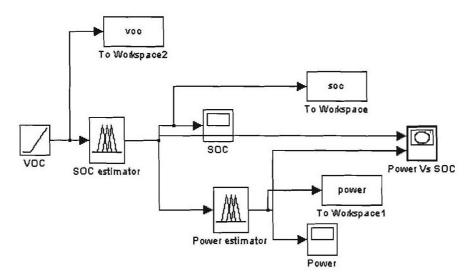


Figure 4: Li ion battery model in MATLAB/Simulink

#### 5. Simulation Results

The SOC, terminal voltage and the power output of the Li ion battery are obtained from the Simulink model. Fig. 5 shows the experimentally measured data (red asterisks) and the fuzzy logic model-predicted results (solid blue line) for the SOC estimation. Fig. 6 shows the experimentally measured data (red asterisks) and the fuzzy logic model-predicted results (solid blue line) for the output power estimation. In

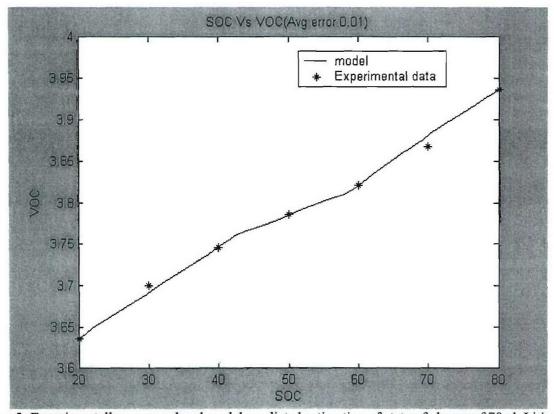


Figure 5: Experimentally measured and model-predicted estimation of state of charge of 70 ah Li-ion cell

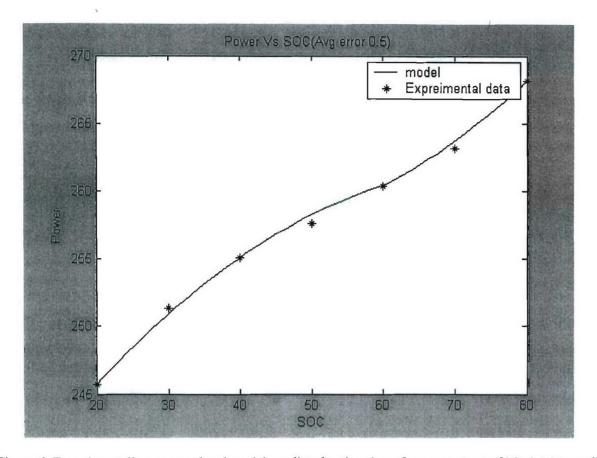


Figure 6: Experimentally measured and model-predicted estimation of power output of 70 ah Li-ion cell

both cases the error between the model-predicted results and experimentally measured results is very small (<1%).

#### 6. Conclusions

In this paper we have presented a fuzzy logic-based Li-ion battery model which has been developed in the MATLAB/Simulink environment using experimentally collected data on 70Ah Kokam Li-ion cells. The model has been validated and the average error of the model is less than 1% when compared with that of the experimental data. The fuzzy logic approach is robust, accurate and reliable. The fuzzy logic battery model can be upgraded to estimate the power output and SOC at different operating temperatures. We have developed diesel generator models in the MATLAB/Simulink environment and are planning to integrate these models together with load models for an unmanned surface sea vehicle to study the performance of this type of hybrid electric vehicle.

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